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Research article

A temporal-causal network model for the effect of emotional charge on information sharing

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A B S T R A C T

In this paper a cognitive model is presented for sharing behaviour (retweeting) on Twitter, addressing the underlying cognitive and affective processes. The model explains how the use of emotions in addition to information can cause an amplification in the diffusion of this information. It was designed according to a Network-Oriented Modeling approach based on temporal-causal network models. By mathematical analysis of stationary points it was verified that the implemented network model does what is expected from the design of the model. In addition, the equilibrium equations of the network model were solved algebraically by a symbolic solver and the solutions were shown to relate well to empirically expected outcomes. Validation by parameter tuning was also performed, and also shows a good approximation of empirically expected outcomes.

Introduction

With the introduction of the Internet, the diffusion of information got an entirely new dimension. Every individual person, organization or community is able to deploy the Internet for their very own communication or information diffusion purposes. Social media or social networking sites, have further strengthened this ability (Ellison and Boyd, 2013). The tremendous successes of the Internet and of these media in recent years have impacted society in terms of public discourse and communication greatly (Boyd and Nicole, 2007). Earlier, the barrier for someone to spread a piece of information through a community was at the cost of the infrastructure required to reach the audience. Since the mass adoption of social media has changed the physical infrastructure of information diffusion, the widespread access to Internet has almost entirely eliminated this barrier.

Nowadays, this has led to huge amounts of information being everywhere and our lives being increasingly determined by analysing and processing this information (Prensky, 2001). However, this massiveness causes that the likelihood of this information actually being diffused and reaching a large audience decreases significantly. The overload of information makes that people can no longer see the wood for the trees (Eppler & Mengis, 2004). Therefore, factors such as characteristics of the sender and the content of the message become more important for the diffusion of the information. Thus, the rise of the Internet and social media have eased the spread of information while simultaneously it made it more difficult to actually reach a large audience.

For several fields, such as marketing and politics, diffusing information among a large audience is vital. Therefore, the question of how diffusion of information can be facilitated and accelerated is very relevant to those fields and has been covered by various studies (e.g., Huffaker, 2010; Nagarajan, Hemant Purohit, & Amit Sheth, 2010). Whereas Huffaker (2010) puts forward the impact of the characteristics of the sender and argues for employing opinion leaders, the others emphasize the effect of adjusting the content of the information, for example, by including photos, videos, or "call-for-actions" (Nagarajan, 2010). Stefan Stieglitz and Dang-Xuan (2013) found that next to content-related features and user and network characteristics, emotions are also an important driver for information diffusion. Specifically, they found that emotionally charged Twitter messages are 'retweeted' (i.e., shared) more often compared to messages without emotional charge. Still more background can be found in (Falk, O'Donnell, and Lieberman, 2012; Falk and Scholz, 2018; Scholz and Falk, 2017).

By focusing on the cognitive and affective processes behind this sharing behaviour from a computational causal modelling perspective, this paper aims to develop a deeper understanding of the empirical findings of Stefan Stieglitz and Dang-Xuan (2013). To achieve this, based on the Network-Oriented Modeling approach described in (Treur, 2016) a temporal-causal network model was designed for a person processing a 'tweet'. This model clearly represents the integrated cognitive and affective processes that explain how the use of emotions can cause an acceleration in the diffusion of information. Example simulations illustrate how emotion indeed affects the spread of the information. The temporal-causal network model has been analysed and verified mathematically on stationary points and equilibria, and validated by comparing it to empirical information.

In the paper, first in Section "Drivers for sharing behaviour on twitter" the drivers for sharing behaviour are discussed in some depth. Next, in Section "The temporal-causal network model" the model is

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introduced, and in Section “Example simulation results” this model is illustrated by example simulations. In Section “Mathematical analysis of the model” it is shown how the model has been verified by mathematical analysis. Section “Validation of the model” shows how validation has been performed. Finally, Section “Discussion” is a discussion section.

Drivers for sharing behaviour on Twitter

In order to develop the temporal-causal model, a comprehensive understanding of the underlying concepts and processes of sharing behaviour on Twitter must be established. Therefore, first, the functioning of sharing on Twitter, i.e. ‘tweeting’ and ‘retweeting’ is explained briefly. Then, the different factors of a tweet that can drive this sharing behaviour are described where after the influence of the driver ‘emotion’ is elaborated in more depth. When a user retweets a tweet, the message is spread to a new set of audiences (i.e. the ‘followers’ of the retweeter). Previous studies have determined that a retweet, in addition to sharing the information, can have functions such as entertaining of a certain audience, e.g. Boyd, Scott Golder, and Gilad Lotan (2010), but in most cases, it functions as publicly agreeing with the message of the tweet (Metaxas et al., 2015).

Sharing behaviour

Whether someone appreciates or agrees with a tweet depends on multiple factors and whether that person is likely to publicly share that agreement, thus to retweet, is depending on even more factors (Suh, Lichan Hong, Peter Pirolli, & Chi, 2010). For this agreement and likeliness to retweet, the content of the information (e.g., the topic and URL or image inclusion), the user and network characteristics (e.g., whether the sender is a peer or an influential person), and the affective dimensions of the messages are important factors. These factors are considered as the drivers of sharing behaviour and are described respectively.

Content-related features that drive sharing behaviour on Twitter are analysed by Nagarajan (2010). They identified that tweets including a “call for some sort of social action” and tweets functioning as “collective group identity-making” or as “crowdsourcing” get significant less retweets than tweets just providing information. Moreover, according to Zhang, Peng, Zhang, Wang, and Zhu (2014), the evaluation of information in these tweets is critical to the sharing behaviour. They found that this evaluation is dependent on the topic of the message, the length of the tweet and the availability of supplementary information such as an URL.

User and network characteristics, or ‘context-related features’ as named by Zhang et al. (2014), are also important drivers for sharing behaviour. They found that the author’s activeness on Twitter influences the readers’ evaluation and appreciation of the tweets positively until the author is overactive which may be regarded as spamming behaviour. Besides, an author’s number of followers positively moderates the impact of his/her degree of activeness on the sharing behaviour of its tweets. Stefan Stieglitz and Dang-Xuan (2013) name these influences according to the concepts of perceived social capital and popularity.

In addition to the content-features and user and network characteristics of the tweet, emotional aspects of messages are also considered as factors influencing sharing behaviour. Stefan Stieglitz and Dang-Xuan (2013) have studied this effect for political Twitter messages and showed that affective dimensions (positive and negative sentiment) positively influence the amount and the time rate of the retweets.

Effect of emotions on sharing behaviour

Almost two decades ago, Bagozzi (1999) analyzed the role emotions in messages and already stated implications of emotions for volitions, goal-directed behaviour, and decisions to help. A bit more recently, Forgas (2006) noted that emotions appear to influence what things we process and how we do that by affecting what we notice, what we learn, what we remember, and the kinds of judgments and decisions we make (p. 273). Zhang et al. (2014) even state that the degree of emotional expression in a post will positively affect its popularity. This is mainly because, in the case of written communication, emotional stimuli (e.g., words or framing) of messages may elicit extensive affective and cognitive processes (Kissler, 2007). These mental processes can account for higher levels of attention and for higher levels of arousal towards the message (Stefan Stieglitz and Dang-Xuan, 2013). Hence, it can be argued that attention- and arousal-related effects caused by emotional stimuli in written messages are determinants of sharing behaviour.

Stefan Stieglitz and Dang-Xuan (2013) found that “the larger the total amount of sentiment (positive or negative) a political Twitter message exhibits, the more often it is retweeted” (p. 240). In their study, this amount of sentiment refers to the amount of words with a positive or negative emotional charge and represents the attitude of the author. To determine this, they conducted a sentiment analysis which is a systematic computer-based analysis of written text.

This role of emotional charge of messages influencing sharing behaviour fits in a more general perspective on the role of emotions in decision making. Decision making is usually based on some form of valuing of a considered decision option. In this valuing process emotions come in: such an option may relate to a positive feeling, and this will affect the decision positively. From a neuroscience perspective, it has been found how such a valuation relates to amygdala activation levels; see, e.g., (Morrison & Salzman, 2010; Murray, 2007; Rangel, Camerer, & Read Montague, 2008; Rudebeck & Murray, 2014; Janak & Tye, 2015).

To summarize, the theoretical foundation for the temporal-causal network model developed in this paper is that next to content-related and user and network characteristics, emotions also drive the decisions underlying information diffusion. The basic premise from a cognitive and neurological perspective is that emotional charge in messages triggers more cognitive involvement by increasing levels of attention and arousal.

The temporal-causal network model

This section describes how a temporal-causal network model was developed according to the theoretical insights described in the previous section. This temporal-causal network model is based on the Network-Oriented Modelling approach described in (Treur, 2016). Causal modelling, causal reasoning and causal simulation have a long tradition in AI; e.g., (Kuipers and Kassirer, 1983; Kuipers, 1984; Pearl, 2000). One of the challenges has been causal modelling involving cyclic graphs; therefore, many approaches limit themselves to Directed Acyclic Graphs (DAG’s). The Network-Oriented Modelling approach based on temporal-causal networks described in (Treur, 2016) can be viewed on the one hand as part of this causal modelling tradition, and on the other hand from the perspective on mental states and their causal relations in Philosophy of Mind; e.g., (Kim, 1996). It is a widely usable generic dynamic AI modelling approach that distinguishes itself by incorporating a dynamic and adaptive perspective, both on states and on causal relations between states. This dynamic perspective takes the form of an added continuous time dimension, and enables modelling of cyclic and adaptive networks, and also of timing of causal effects. Due to this, causal reasoning and simulation is possible for adaptive networks for connected mental states, or networks for (evolving) social interaction.

According to the adopted Network-Oriented Modelling approach, a model is designed at a conceptual level, for example, in the form of a graphical conceptual representation or a conceptual matrix representation. A graphical conceptual representation displays nodes for *states* and arrows for *connections* indicating causal impacts from one state to another, and includes additional information in the form of:

- for each connection from a state X to a state Y a *connection weight* $\boldsymbol{\omega}_{X,Y}$ (for the strength of the impact of X on Y)
- for each state Y a *speed factor* $\boldsymbol{\eta}_Y$ (for the timing of the effect of the impact)
- for each state Y the type of *combination function* $\mathbf{c}_Y(..)$ used (to aggregate multiple impacts on a state)

To choose combination functions, a number of standard options is available, varying from linear or sum functions or logistic functions, to product or max and min-based functions as often used in probabilistic and possibilistic approaches. The conceptual representation of a model which basically is a labelled graph with the three types of labels listed above, can be transformed in a systematic or automated standard manner into an equivalent declarative numerical representation as follows (Treur, 2016, Ch 2); here the variable t indicates a time point; it varies over the real numbers.

- at each time point t each state Y in the model has a real number value $Y(t)$ (usually in the interval [0, 1])
- at each time point t each state X connected to state Y has an impact on Y defined as $\mathbf{impact}_{X,Y}(t) = \omega_{X,Y}X(t)$ where $\boldsymbol{\omega}_{X,Y}$ is the weight of the connection from X to Y
- The *aggregated impact* of multiple states X_i on Y at t is determined using a *combination function* $\mathbf{c}_Y(..)$:

$$\mathbf{aggimpact}_Y(t) = \mathbf{c}_Y(\mathbf{impact}_{X_1,Y}(t), \; ..., \mathbf{impact}_{X_k,Y}(t)) = \mathbf{c}_Y(\omega_{X_1,Y}X_1(t), \; ..., \quad _{X_k,Y}X_k(t))$$

where X_i are the states with connections to state Y

- The effect of $\mathbf{aggimpact}_y(t)$ on Y is exerted over time gradually, depending on speed factor $\boldsymbol{\eta}_Y$:

$$Y(t \;+\Delta\; t) = Y(t) + \eta_Y[\mathbf{aggimpact}_Y(t) - Y(t)]\Delta t$$

$$\frac{dY(t)}{dt} = \eta_Y[\;\mathbf{aggimpact}_Y(t) - Y(t)]$$

- This provides a *difference* and *differential equation* for Y:

$$Y(t \;+\; \Delta t) = Y(t) + Y[\mathbf{c}_Y(\omega_{X_1,Y}X_1(t), \; ..., \omega_{X_k,Y}X_k(t)) - Y(t)]\Delta t$$

$$\frac{dY(t)}{dt} = \eta_Y[\;\mathbf{c}_Y(\omega_{X_1,Y}X_1(t), \; ... \;, \omega_{X_k,Y}X_k(t)) - Y(t)]$$

These numerical representations can be used for mathematical and computational analysis and simulation. Software templates are available, for example, in Matlab and Python to support the transition from conceptual to numerical representation described above in a fully automated manner.

A conceptual network model, depicted in Fig. 1, was constructed that focuses on the emotion and information in tweets and their effects on a person's retweeting behaviour. Nine different states are distinguished, inter-connected by directional connections that indicate the causal relations.

In an effort to gain a clear understanding of the relations between the states and connections in this representation, a scenario is used to illustrate the relations of each state. In this scenario, we have two persons: Mark and Tim. Mark sends out a tweet in which he expresses that he cannot wait to sing in the Christmas choir next week. This tweet contains both information and emotional charge: there is a choir performance next week, and secondly, Mark makes clear that he cannot wait for this event to happen. Tim reads Mark's tweet. Tim's interpretation of this message is positively influenced by the fact that Mark and Tim are friends. Tim does like to visit choir performances; therefore, he already has a positive association on the information that this event will take place. Reading about this Christmas performance, Tim gets slightly aroused and is focusing on the message. Mark's enthusiasm amplifies Tim's attention and arousal, which in turn lead to a positive interpretation of the tweet. Tim's positive interpretation of the message coupled with the fact that he is good friends with Mark and is excited about this performance leads to Tim's decision to retweet Mark's original Tweet. In the presented model, states have a state value ranging from 0 to 1. For example, a value 0 for the state emotional charge implies an absence of emotional charge, whereas a value 1 for emotional charge represents the maximal amount of emotional charge.

Table 1 describes the weights of the connections in the conceptual representation. In this table each cell (X, Y) in row X and column Y shows the weight of the connection from state X to state Y. Connection weights range here from 0 (no connection) to 1 (strong connection), chosen in incremental steps of 0.25. Person, Information known and Emotional charge have a maximal influence on Relation with person, Opinion, Attention and Arousal, respectively, as these are the influencers. The extent of positive interpretation has a strong influence on the appreciation of the person of the incoming tweet. A person's internal attention and arousal are stronger influencers on the interpretation than the person's relation with the sender. In line with what both Stefan Stieglitz and Dang-Xuan (2013), and Kim and Yoo (2012) indicate about emotions being a strong driver for information diffusion, attention and arousal are modelled as stronger influencers than the relation with the person.

Next, a declarative numerical representation of the presented network and its dynamics is discussed using first-order differential equations and difference equations. Not only can different connections have different weights, the expected behaviour might also differ per state. Different combination functions are considered to fit behavioural expectations. For states with a single impact, an identity function $\mathbf{id}(V) = V$ is used. For states with multiple impacts, a scaled sum combination function is used, defined as:

$$\mathbf{ssum}_\lambda(V_1, \; ..., \; V_k) = \frac{V_1 + \; ... + \; V_k}{\lambda}$$

For the states Interpretation and Sharing behaviour, as an alternative also an advanced logistic combination function has been used, defined as:

$$\mathbf{alogistic}_{\sigma\tau}(V_1, \; ..., \; V_k) = \left[\frac{1}{1 + \mathbf{e}^{\;-\sigma(V_1 + .. + V_k \;\; -\tau)}} - \frac{1}{1 + \mathbf{e}^{\sigma\tau}}\right](1 + \mathbf{e}^{-\sigma\tau})$$

with σ a steepness and τ a threshold parameter. Depending on the steepness σ this allows a more binary 0 or 1 outcome than a scaled sum function. As according to the modelling approach followed, such a combination function is just a label or parameter in the model, it is easy to switch from one to the other, and the software templates support that.

The difference equation for the state 'Relation' is as follows (based on the identity combination function):

$$\text{Relation}(t \;+\; \Delta t) = \text{Relation}(t) + \eta_{\text{Relation}}[\;\omega_{\text{Person,Relation}}\text{Person}(t) - \text{Relation}(t)]\Delta t$$

The differential equivalent of this equation is:

$$\frac{d\text{Relation}(t)}{dt} = \eta_{\text{Relation}}[\omega_{\text{Person,Relation}}\text{Person}(t) - \text{Relation}(t)]$$

Note that Person indicates the closeness of the friendship with the sender.

For Opinion, a scaled sum combination function is used:

$$\text{Opinion}(t \;+\Delta\; t) = \text{Opinion}(t) + \eta_{\text{Opinion}}\left[\frac{\omega_{\text{Information,Opinion}}\;\text{Information}(t) + \omega_{\text{Interpretation,Opinion}}\;\text{Interpretation}(t)}{\lambda} - \text{Opinion}(t)\right]\Delta t$$

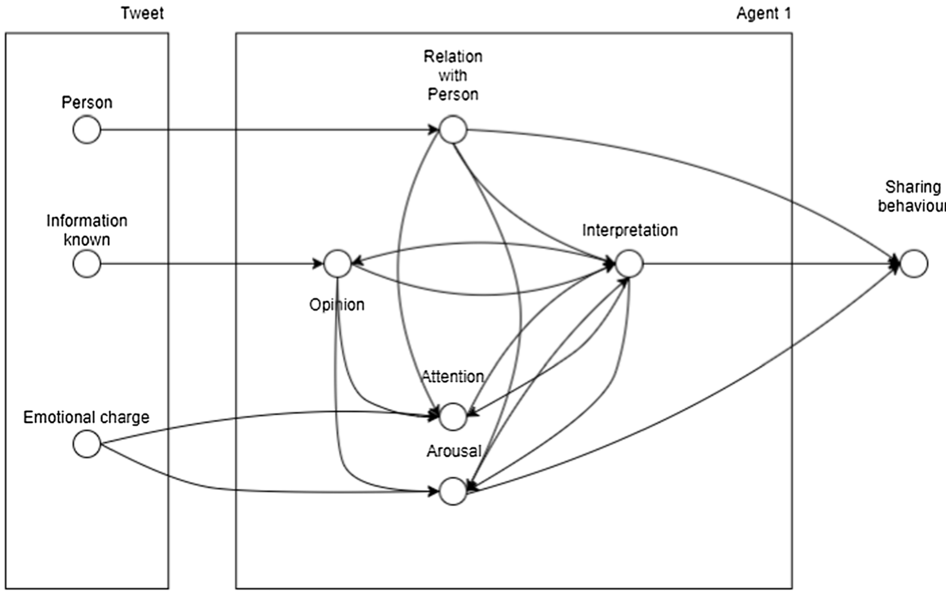

Fig. 1. Conceptual representation of the network model.

Table 1
Connection matrix in the conceptual representation (screen display).

	States and connections	X_1 Person	X_2 Information	X_3 Emotion	X_4 Relation	X_5 Opinion	X_6 Interpret	X_7 Attention	X_8 Arousal	X_9 Sharing
X_1	Person	0	0	0	1	0	0	0	0	0
X_2	Information	0	0	0	0	1	0	0	0	0
X_3	Emotion	0	0	0	0	0	0	1	1	0
X_4	Relation	0	0	0	0	0	0.5	0.25	0.25	0.5
X_5	Opinion	0	0	0	0	0	0.75	0.25	0.25	0
X_6	Interpretation	0	0	0	0	0.75	0	0.25	0.25	1
X_7	Attention	0	0	0	0	0	0.75	0	0	0
X_8	Arousal	0	0	0	0	0	0.75	0	0	1
X_9	Sharing	0	0	0	0	0	0	0	0	0

(2012) indicate about emotions being a strong driver for information diffusion, attention and arousal are modelled as stronger influencers than the relation with the person.

The differential equivalent of this equation is:

$$\frac{d\text{Opinion}(t)}{dt} = \eta_{\text{Opinion}}\left[\frac{\omega_{\text{Information,Opinion}}\text{Information}(t) + \omega_{\text{Interpretation,Opinion}}\ \text{Interpretation}(t)}{\lambda} - \text{Opinion}(t)\right]$$

For Sharing behaviour, using an advanced logistic combination function the difference equation is:

$$\begin{aligned}\text{Sharing}(t + \Delta t) = \text{Sharing}(t) &+ \eta_{\text{Sharing}}\ [\textbf{alogistic}_{\sigma\tau}(\omega_{\text{Relation,Sharing}}\\ &\text{Relation}(t),\ \omega_{\text{Interpretation,Sharing}}\\ &\text{Interpretation}(t),\ \omega_{\text{Arousal,Sharing}}\text{Arousal}(t))\\ &- \text{Sharing}(t)]\Delta t\end{aligned}$$

The differential equivalent is:

$$\begin{aligned}\frac{d\text{Sharing}(t)}{dt} = \eta_{\text{Sharing}}\ [&\textbf{alogistic}_{\sigma\tau}(\omega_{\text{Relation,Sharing}}\text{Relation}(t),\\ &\omega_{\text{Interpretation,Sharing}}\text{Interpretation}(t),\ \omega_{\text{Arousal,Sharing}}\text{Arousal}(t))\\ &- \text{Sharing}(t)]\end{aligned}$$

A concise overview of all 6 differential equations for the non-input states (based on the scaled sum combination function for states with multiple impacts) can be found in Box 1.

Example simulation results

In this section, simulations for three different scenarios are shown. For Interpretation and Sharing behaviour, the advanced logistic combination function has been used. The first simulation (Fig. 2) shows a scenario where a person receives a tweet with no emotional charge. The

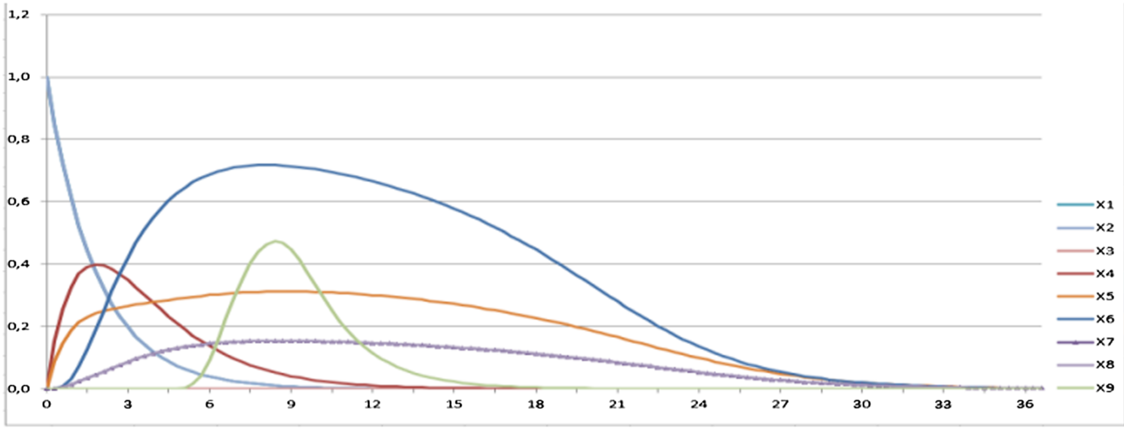

Fig. 2. Simulation without emotional charge; value of $X_3 = 0$.

green line (X_9) indicates the Sharing behaviour. In all simulations, the assumption is made that a person retweets a tweet when the value of Sharing reaches at least 0.9.

Box 1

Overview of the differential equations

$$\frac{d\text{Relation}}{dt} = \eta_{\text{Relation}}\,[\omega_{\text{Person,Relation}}\text{Person}-\text{Relation}]$$

$$\frac{d\text{Opinion}}{dt} = \eta_{\text{Opinion}}\left[\frac{\omega_{\text{Information,Opinion}}\text{Information} + \omega_{\text{Interpretation,Opinion}}\ \text{Interpretation}}{\lambda_{\text{Opinion}}}-\text{Opinion}\right]$$

$$\frac{d\text{Interpretation}}{dt} = \eta_{\text{Interpretation}}\left[\frac{\omega_{\text{Re lation,Interpretation}}\ \text{Re lation} + \omega_{\text{Opinion,Interpretation}}\ \text{Opinion} + \omega_{\text{Attention,Interpretation}}\ \text{Attention},}{\lambda_{\text{Interpretation}}}-\text{Interpretation}\right]$$

$$\frac{d\text{Attention}}{dt} = \eta_{Attention}\left[\frac{\omega_{\text{Emotion,Attention}}\text{Emotion} + \omega_{\text{Relation,Attention}}\text{Relation} + \omega_{\text{Opinion,Attention}}\text{Opinion}}{\lambda_{\text{Attention}}}-\text{Attention}\right]$$

$$\frac{d\text{Arousal}}{dt} = \eta_{\text{Arousal}}\left[\frac{\omega_{\text{Emotion,Arousal}}\text{Emotion} + \omega_{\text{Relation,Arousal}}\text{Relation} + \omega_{\text{Opinion,Arousal}}\text{Opinion} + \omega_{\text{Intepretation,Arousal}}\text{Intepretation}}{\lambda_{\text{Arousal}}}-\text{Arousal}\right]$$

$$\frac{d\text{Sharing}}{dt} = \eta_{\text{Sharing}}\ [\textbf{alogistic}_{\sigma\tau}(\omega_{\text{Relation,Sharing}}\text{Relation},\ \omega_{\text{Interpretation,Sharing}}\text{Interpretation},\ \omega_{\text{Arousal,Sharing}}\text{Arousal}$$

The second simulation (Fig. 3) shows a scenario with a tweet that contains a small amount of emotion, and the third simulation (Fig. 4) shows a scenario with a received tweet containing the maximum amount of emotion. By looking at the plots, it can be noticed that emotion added to a tweet indeed leads to a higher activation of the retweet action. (See Fig. 5)

Mathematical analysis of the model

Mathematical Analysis of the model was performed in two different ways. First, analysis of stationary points was done in order to verify the implemented model against the model specification. Next, overall equilibria for the model were analysed. Symbolic expressions were found for the equilibrium values of each state in terms of the connection weights and input values of Person, Information and Emotion.

Definition. A state Y has a *stationary point* at t if $dY(t)/dt = 0$. A model is in *equilibrium* a t if every state Y of the model has a stationary point at t.

For a temporal-causal network model the following criterion in terms of the labels for connection weights and combination functions can be derived (e.g., (Treur, 2016), Ch 12).

Criterion for a temporal-causal network model

A state Y in a temporal-causal network model has a *stationary point* at t if and only if

$$\mathbf{c}_Y(\omega_{X_1,Y}X_1(t),\ \ldots\ ,\ \omega_{X_k,Y}X_k(t)) = Y(t)$$

where X_i are the states with outgoing connections to state Y.

The temporal-causal network model is in *equilibrium* at t if and only if this holds for all states. In this case the above criterion expressions for all states together form the *equilibrium equations* of the network model.

Verification based on analysis of stationary points was done for a scenario with maximal emotional charge. The results of this analysis can be found in Table 2.

Here the third row (**Agg. impact**) indicates the left-hand side of the stationary point criterion, and the second row (**State value**) the right-hand side. For most states, the accuracy is within acceptable boundaries, but the stationary point calculation for state Relation (X_4) is off by over 5%. This is explained by the narrow maximum of X_4 (see the red line in Fig. 3). To increase accuracy, the step size of the model may be

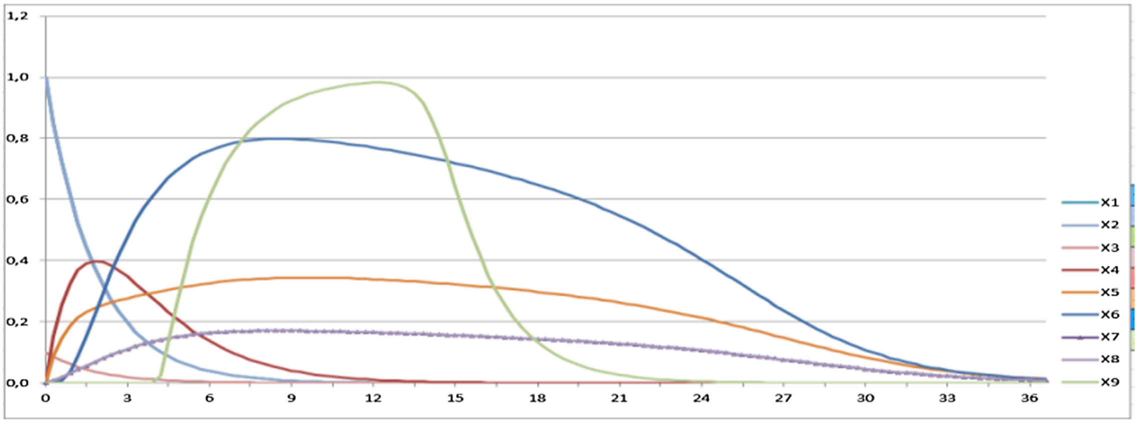

Fig. 3. Simulation with low emotional charge; starting value of $X_3 = 0.1$.

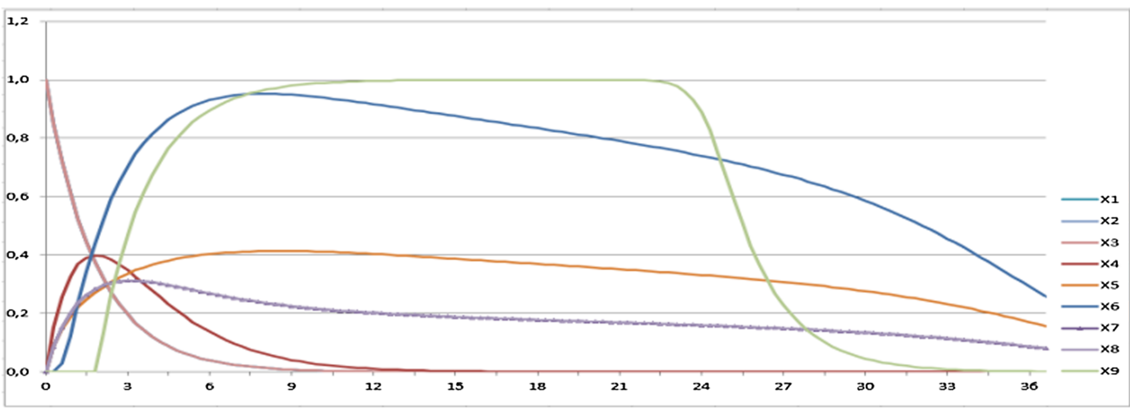

Fig. 4. Simulation with high emotional charge; starting value of $X_3 = 1$.

decreased from the current step size $\Delta t = 0.3$ to, for example, $\Delta t = 0.1$. For X_4 and X_9, no table entries are provided; both the state values and aggregated impacts are zero.

Next, the overall equilibrium equations were identified; see Box 2. Note that in such an equilibrium state it is assumed that the input values of Person, Information and Emotion are constant over time, with values indicated by A_1, A_2, A_3, respectively. Note also that Sharing behaviour causally depends on the other states but not conversely; its equilibrium value can directly be calculated from the equilibrium values of the other states Relation, Interpretation and Arousal, given any choice of combination function.

Box 2

Equilibrium Equations of the network model

$$\text{Relation} = \omega_{\text{Person,Relation}}\text{Person}$$

$$\text{Opinion} = \frac{\omega_{\text{Information,Opinion}}\text{Information} + \omega_{\text{Interpretation,Opinion}}\text{Interpretation}}{\lambda_{\text{Opinion}}}$$

$$\text{Interpretation} = \frac{\omega_{\text{Relation,Interpretation}}\text{Relation} + \omega_{\text{Opinion,Interpretation}}\text{Opinion} + \omega_{\text{Attention,Interpretation}}\text{Attention}}{\lambda_{\text{Interpretation}}}$$

$$\text{Attention} = \frac{\omega_{\text{Emotion,Attention}}\text{Emotion} + \omega_{\text{Relation,Attention}}\text{Relation} + \omega_{\text{Opinion,Attention}}\text{Opinion} + \omega_{\text{Interpretation,Attention}}\text{Interpretation}}{\lambda_{\text{Attention}}}$$

$$\text{Arousal} = \frac{\omega_{\text{Emotion,Arousal}}\text{Emotion} + \omega_{\text{Relation,Arousal}}\text{Relation} + \omega_{\text{Opinion,Arousal}}\text{Opinion} + \omega_{\text{Interpretation,Arousal}}\text{Interpretation}}{\lambda_{\text{Arousal}}}$$

$$\text{Sharing} = \textbf{alogistic}\sigma\tau(\omega_{\text{Relation,Sharing}}\text{Relation},\ \omega_{\text{Interpretation,Sharing}}\text{Interpretation},\ \omega_{\text{Arousal,Sharing}}\text{Arousal})$$

For example, for the advanced logistic combination function the equilibrium value is

$$\text{Sharing} = X_9 = \textbf{alogistic}_{\sigma,\tau}(\omega_{\text{Relation,Sharing}}\ \text{Relation},\ \omega_{\text{Interpretation,Sharing}}\ \text{Interpretation},\ \omega_{\text{Arousal,Sharing}}\ \text{Arousal})$$

The linear equilibrium equations for the states other than Sharing can be solved in a symbolic manner to obtain explicit algebraic expressions for their equilibrium values (the online WIMS Linear Solver tool[1] was used); see Box 3. Here subscripts are abbreviated for the sake of briefness.

Box 3

Explicit algebraic solutions of the equilibrium equations of the network model

$$\textbf{Person} = X_1 = A_1 \quad \textbf{Information} = X_2 = A_2 \quad \textbf{Emotion} = X_3 = A_3$$

$$\textbf{Relation} = X_4 = \omega_{P,R} A_1$$

[1] http://wims.unice.fr/wims/wims.cgi?session=DH1DFC9A6E.3&+lang=en&+module=tool%2Flinear%2Flinsolver.en.

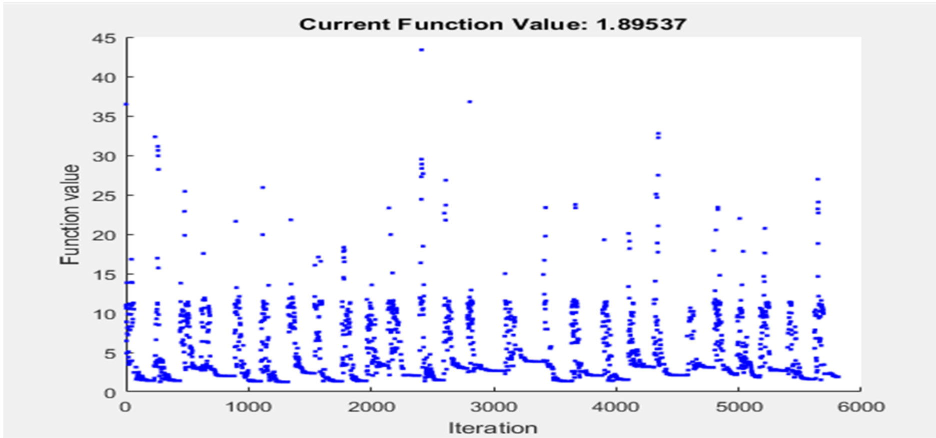

Fig. 5. Pattern of SSR during the Simulated Annealing.

Table 2
Mathematical verification results for stationary points.

	X_4 (Relation)	X_5 (Opinion)	X_6 (Interpretation)	X_7 & X_8 (Attention & Arousal)	X_9 (Sharing)
Time point	1.8	8.7	8.1	3.0	19.2
State value	0.39933	0.41378	0.95215	0.31218	0.99990
Agg. impact	0.37715	0.41245	0.94834	0.31044	0.99990
Deviation	0.02218	0.00133	0.00381	0.00174	0
Accuracy	94.12%	99.68%	99.60%	99.44%	100%

$$\begin{aligned}\textbf{Opinion} = X_5 = &-[A_1\omega_{Int,O}\omega_{P,R}(\lambda_{Ar}\lambda_{At}\omega_{R,Int} + \lambda_{Ar}\omega_{At,Int}\omega_{RAt} \\ &+ \lambda_{At}\omega_{Ar,Int}\omega_{R,Ar}) + A3(\lambda_{Ar}\omega_{At,Int}\omega_{E,At} \\ &+ \lambda_{At}\omega_{Ar,Int}\omega_{E,Ar})\omega_{Int,O} + A_2\omega_{Inf,O}((-\lambda_{Ar}\omega_{At,Int}\omega_{Int,At}) \\ &- \lambda_{At}\omega_{Ar,Int}\omega_{Int,Ar} + \lambda_{Ar}\lambda_{At}\lambda_I)] \\ &/[\omega_{Int,O}(\lambda_{Ar}\lambda_{At}\omega_{O,Int} + \lambda_{Ar}\omega_{At,Int}\omega_{O,At} + \lambda_{At}\omega_{Ar,Int}\omega_{O,Ar}) \\ &+ \lambda_O(\lambda_{Ar}\omega_{At,Int}\omega_{Int,At} + \lambda_{At}\omega_{Ar,Int}\omega_{Int,Ar} - \lambda_{Ar}\lambda_{At}\lambda_I)]\end{aligned}$$

$$\begin{aligned}\textbf{Interpretation} = X_6 = &-[A_1\lambda_O\omega_{P,R}(\lambda_{Ar}\lambda_{At}\omega_{R,Int} + \lambda_{Ar}\lambda_{At,Int}\omega_{R,At} \\ &+ \lambda_{At}\omega_{Ar,Int}\omega_{R,Ar}) + A_2\omega_{Inf,O}(\lambda_{Ar}\lambda_{At}\omega_{O,Int} \\ &+ \lambda_{Ar}\omega_{At,Int}\omega_{O,At} + \lambda_{At}\omega_{Ar,Int}\omega_{O,Ar}) \\ &+ A_3\lambda_O(\lambda_{Ar}\omega_{At,Int}\omega_{E,At} + \lambda_{At}\omega_{Ar,Int}\omega_{E,Ar})] \\ &/[\omega_{Int,O}(\lambda_{Ar}\lambda_{At}\omega_{O,Int} + \lambda_{Ar}\omega_{At,Int}\omega_{O,At} \\ &+ \lambda_{At}\omega_{Ar,Int}\omega_{O,Ar}) + \lambda_O(\lambda_{Ar}\omega_{At,Int}\omega_{Int,At} \\ &+ \lambda_{At}\omega_{Ar,Int}\omega_{Int,Ar} - \lambda_{Ar}\lambda_{At}\lambda_I)]\end{aligned}$$

$$\begin{aligned}\textbf{Attention} = X_7 \\ = &-[A_1\omega_{P,R}(\omega_{Int,O}(\lambda_{Ar}\omega_{O,At}\omega_{R,Int} + \omega_{Ar,Int}(\omega_{O,At}\omega_{R,Ar} \\ &- \omega_{O,Ar}\omega_{R,At}) - \lambda_{Ar}\omega_{O,Int}\omega_{R,At}) \\ &+ \lambda_O(\lambda_{Ar}\omega_{Int,At}\omega_{R,Int} + \omega_{Ar,Int}(\omega_{Int,At}\omega_{R,Ar} - \omega_{Int,Ar}\omega_{R,At}) \\ &+ \lambda_{Ar}\lambda_I\omega_{R,At})) \\ &+ A_3(\omega_{Int,O}(\omega_{Ar,Int}(\omega_{E,Ar}\omega_{O,At} - \omega_{E,At}\omega_{O,Ar}) \\ &- \lambda_{Ar}\omega_{E,At}\omega_{O,Int}) + \lambda_O(\omega_{Ar,Int}(\omega_{E,Ar}\omega_{Int,At} - \omega_{E,At}\omega_{Int,Ar}) \\ &+ \lambda_{Ar}\lambda_I\omega_{E,At})) + A_2\omega_{Inf,O}(\lambda_{Ar}\omega_{Int,At}\omega_{O,Int} \\ &+ \omega_{Ar,Int}(\omega_{Int,At}\omega_{O,Ar} - \omega_{Int,Ar}\omega_{O,At}) + \lambda_{Ar}\lambda_I\omega_{O,At})] \\ &/[\omega_{Int,O}(\lambda_{Ar}\lambda_{At}\omega_{O,Int} + \lambda_{Ar}\omega_{At,Int}\omega_{O,At} + \lambda_{At}\omega_{Ar,Int}\omega_{O,Ar}) \\ &+ \lambda_O(\lambda_{Ar}\omega_{At,Int}\omega_{Int,At} + \lambda_{At}\omega_{Ar,Int}\omega_{Int,Ar} - \lambda_{Ar}\lambda_{At}\lambda_I)]\end{aligned}$$

$$\begin{aligned}\text{Arousal} = X_8 = &-[A_1\omega_{P,R}(\omega_{Int,O}(\lambda_{At}\omega_{O,Ar}\omega_{R,Int} \\ &+ \omega_{At,Int}(\omega_{O,Ar}\omega_{R,At} - \omega_{O,At}\omega_{R,Ar}) - \lambda_{At}\omega_{O,Int}\omega_{R,Ar}) \\ &+ \lambda_O(\lambda_{At}\omega_{Int,Ar}\omega_{R,Int} + \omega_{At,Int}(\omega_{Int,Ar}\omega_{R,At} - \omega_{Int,At}\omega_{R,Ar}) \\ &+ \lambda_{At}\lambda_I\omega_{R,Ar})) \\ &+ A_3(\omega_{Int,O}(\omega_{At,Int}(\omega_{E,At}\omega_{O,Ar} - \omega_{E,Ar}\omega_{O,At}) \\ &- \lambda_{At}\omega_{E,Ar}\omega_{O,Int}) + \lambda_O(\omega_{At,Int}(\omega_{E,At}\omega_{Int,Ar} - \omega_{E,Ar}\omega_{Int,At}) \\ &+ \lambda_{At}\lambda_I\lambda_{E,Ar}))\end{aligned}$$

As can be seen, each of the equilibrium values is a linear combination of the three values A_1, A_2, A_3, where the coefficients are expressed in terms of specific connection weights and scaling factors. For example, this means that if all of these values A_1, A_2, A_3 are reduced by 20%, all equilibrium values will be reduced by 20%. This indeed is the case in simulation examples. If the values of the parameters for connection weights are assigned as in Table 1 and scaling factors $\lambda_{Ar} = 1.75$, $\lambda_{Ar} = 1.75$, $\lambda_O = 1.75$ and $\lambda_I = 2.75$, then the outcomes of the equilibrium values are (here the green highlighted digits are repetitive):

Person=$X_1 = A_1$
Information=$X_2 = A_2$
Emotion=$X_3 = A_3$

Relation $= X_4 = A_1$

Opinion $= X_5 = 0.17307692A_3 + 0.682692307A_2 + 0.144230769A_1$

Interpretation $= X_6 = 0.40384615A_3 + 0.259615384A_2 + 0.336538461A_1$

Attention $= X_7 = 0.65384615A_3 + 0.13461538A_2 + 0.21153846A_1$

Arousal $= X_8 = 0.65384615A_3 + 0.13461538A_2 + 0.21153846A_1$

It can be seen that each of these equilibrium state values is a weighted average of A_1, A_2, and A_3 (for each the sum of these weights is 1). Therefore, in particular when all A_i are 1, all of these outcomes are

Table 3
Initial and final speed factors used for parameter tuning.

	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9
η initially	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
η after tuning	0.434	0.364	0.979	0.853	0.324	0.792	0.954	0.610	0.210

1. If only A_1 and A_2 are 1, then the outcomes depend just on the emotional charge A_3:

Person=X_1 = 1.0
Information=X_2 = 1.0
Emotion = X3 = A3

Relation = X_4 = 1.0

Opinion = $X_5 = 0.17307692A_3 + 0.82692307$

Interpretation = $X_6 = 0.40384615A_3 + 0.59615384$

Attention = $X_7 = 0.6538461A_3 + 0.3461538$

Arousal = $X_8 = 0.6538461A_3 + 0.3461538$

Sharing = $X_9 = \mathbf{alogistic}\sigma, \tau(0.5,\ 0.40384615A_3 + 0.59615384,\ 0.6538461A_3 + 0.3461538)$

It can be seen from this that the equilibrium values of Attention and Arousal depend for about 65% on the emotional charge level and as a consequence the impact of the emotional charge on the equilibrium value of Interpretation is about 40%. The effect of emotional charge on Sharing works through two causal pathways: via Interpretation and via Arousal. This leads to the function

$$\mathbf{alogistic}_{\sigma,\tau}(0.5,\ 0.40384615A_3 + 0.59615384,\ 0.6538461A_3 + 0.3461538)$$

which is a monotonically increasing function of A_3. So more emotional charge (higher A_3) leads to more sharing. In this way, together these states Attention and Arousal can make the difference for Sharing to pass the threshold for retweeting, if the emotional charge level A_3 is high enough. Using appropriate values for steepness and threshold in this combination function **alogistic**, (..)can modulate or amplify the effect and realise an increase as known from empirical literature. More specifically, by Stefan Stieglitz and Dang-Xuan (2013) it is found:

- *One-unit increase in total amount of sentiments = 6% more retweets*

Here, one-unit increase in the total amount of sentiments is measured by the tool 'SentiStrength' (Thelwall, 2011), which ranges from 0 to 9, so for the whole scale the difference is 60%. This can well be approximated by the above Mathematical Analysis of the equilibria by choosing appropriate values for steepness and threshold of the logistic sum combination function used for Sharing. In particular, if in the above $\mathbf{alogistic}_{\sigma,\tau}$**(..)** formula of Sharing dependent on A_1, steepness $\sigma = 2.5$ and threshold $\tau = 1.25$ are chosen, then without emotional charge ($A_1 = 0$) Sharing = 0.601142, and with emotional charge ($A_1 = 1$) Sharing = 0.956063, which is 59% higher (0.956063/ 0.601142 = 1.59, so the difference is 59% of the value 0.601142); this shows how the model can easily approximate the empirically found 60%.

Validation of the model

For validating the model dynamically, as no suitable (temporal) empirical data was found, the requirement of 60% difference found by Stefan Stieglitz and Dang-Xuan (2013) was used here as well (see at the end of Section "Mathematical analysis of the model"). Simulation of the model without emotional charge (Initial value 0) was compared with a model with maximal emotion (Initial value 1). To get data points for sharing without emotional charge, the values for a simulation of X_9 with maximal emotion were multiplied by 0.4. Thus, the required values for X_9 without emotional charge are 60% lower than the output values of X_9 with maximum emotion. By comparing this data set against model simulations, the sum of squares of residuals SSR can be obtained as an indication how far the model is off. To get an approximation, parameter tuning was performed in Matlab, for tuning each speed factor **η**. By the tuning process SSR was reduced to 17.01 and average (root mean square) deviation $\left(\frac{SSR}{n}\right) = 0.125$. Table 3 shows initial and tuned speed factors. The outcome was that a 60% higher effect of emotional charge than without emotional charge, is approximated up to 0.125, which is a fairly good result.

Discussion

The aim of this paper was to analyse the underlying processes using emotional charge in Twitter messages and to show the effects on information diffusion. This was done through the development of a temporal-causal network model. Different simulations show how retweeting behaviour changes, and may be used for industries to adapt social media marketing strategies to achieve a higher diffusion of information. The model indeed predicts that higher emotional charge causes more sharing.

By mathematical analysis of stationary points it was verified that the implemented network model does what is expected from the design of the model. In addition, the equilibrium equations of the network model were solved algebraically by a symbolic solver. This has provided a monotonically increasing formula in terms of the level of emotional charge predicting the sharing behaviour, which has been compared to empirical data showing a good match. Validation by parameter tuning was also performed, and also shows a good approximation of empirically expected outcomes. More specifically, a requirement of 6% *more* retweets for each unit increase (hence 60% more for the whole scale) in emotional charge, was found in the paper of Stefan Stieglitz and Dang-Xuan (2013). Both by the equilibrium equations and by parameter tuning it was found that the model can approximate this empirically found effect well.

The model provides insights to marketers on what extents of emotional charge can influence information diffusion and how this charge also affects the other drivers of sharing behaviour. Based on these insights, marketers could develop tools that evaluate messages on their effectiveness and that forecast the information diffusion patterns that should emerge from certain messages.

More and more information becomes available from neuroscience. The model can be validated, further developed and refined by involving new recent developments, for example, as described in (Baek, Christin Scholz, Brook O'Donnell, & Falk, 2017; Falk et al., 2012; Falk and Scholz, 2018; Scholz and Falk, 2017). Based on such literature future refinements of the model may be developed incorporating elements of a more detailed (subjective) valuing system for deciding, self-related processing, and social cognition with respect to receivers of the message (empathy, Theory of Mind, mentalizing).

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